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A Framework for Tool Condition Monitoring of Abrasive Waterjet Systems

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Abstract

The study presents an innovative method for developing a waterjet mixing tube process monitoring system, leveraging aluminium oxide abrasives for accelerated data collection. A novel method of recording data during the jet dwell cycle is proposed, which eliminates abrasive from the data collection step and allows for the mixing tube wear state to be predicted before machining takes place. Airflow sensors were shown to be capable of detecting changes in mixing tube exit diameter. The performance of machine learning models, utilizing airflow data, was compared against simpler models using wear time as a sole parameter. Both approaches were tested in their ability to predict the exit diameter and to classify the state of the tool. Although wear time-based models outperformed machine learning models in this study, their ability to adapt to process changes may be limited. Machine learning models, given a larger dataset, may be required for accurate wear detection. The research lays a promising foundation for developing a robust mixing tube monitoring system. Future work should focus on collecting more data, investigating the effect of mixing chamber and orifice wear on the airflow signal, and evaluating model performance trained with accelerated wear data, on tubes worn in a regular wear trial.

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Keywords: Process monitoring; Abrasive waterjet; Machining; Machine learning; Data collection

1. Introduction

The abrasive waterjet is a diverse non-conventional machining process. It can cut a broad range of materials without altering their physical properties. Despite its many advantages, there is a need for effective process monitoring of the nozzle tool, which suffers from wear.

The nozzle, the tool and critical component of the waterjet system, comprises three key components: the orifice, mixing chamber, and mixing tube. First the orifice focusses the high-pressured jet of water, then abrasive particles are introduced in the mixing chamber, finally abrasives are accelerated and mixed with water in the mixing tube. Continuous abrasive impact with the tube walls wears its inner profile, resulting in a reduction in cutting performance [1], [2].

Real-time monitoring of mixing tube wear promises to be an effective approach to maximise the life of the waterjet tools and reduce waste attributed to machining with a worn tool. Moreover, it paves the way for automating the machining process and designing a sustainable mixing tube replacement strategy.

Creating a mixing tube monitoring system presents several significant challenges. Firstly, the proposed system must be non-intrusive, capable of functioning online without process interruption. The monitoring system needs to function in a harsh environment with high humidity. Secondly, the system must navigate the large input parameter space which includes

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abrasive, jet, and workpiece properties. Finally, considering a mixing tube life of approximately 50-100 hours, when machining with the standard garnet material, the data collection process can become expensive and time consuming [3].

As a result of these challenges, research has prioritized exploring whether different sensors can differentiate between an unworn and worn tool. However, the emphasis needs to shift to effectively predicting the extent of tool wear. In this context, machine learning emerges as a potential candidate for tool wear prediction. The performance of machine learning solutions should be compared to simple approaches of recording the time the tool has been used – to justify the use of different sensors and the data collection process.

The paper aims to present novel preliminary research aimed at developing a mixing tube process monitoring system. The first objective is to develop a framework for data collection for this system, overcoming the outlined challenges. The second objective is to evaluate the performance of machine learning models in both tool wear prediction and tool state classification using airflow sensor data.

The structure of this paper is as follows:

- Literature around abrasive waterjet process monitoring and mixing tube wear is reviewed.
- The design of a framework for a data collection system is presented together with the experimental methodology and the data analysis steps used.
- The results of the study are discussed before conclusions are drawn.

2. Literature review

2.1. Process monitoring of the abrasive waterjet.

The first challenge in developing a process monitoring system for the abrasive waterjet is that the system must be feasible. The process must be non-intrusive, affordable, and able to function in the harsh waterjet environment.

When monitoring wear, detection can be performed via a direct or indirect approach. Direct methods include measuring the exit diameter of the nozzle through pin gages, measuring the weight loss of the nozzle or studying the bore profile through radiometric techniques or destructive longitudinal sectioning of the tube [1], [4]–[6]. The exit diameter measurement is non-destructive, simple to perform and does not require removing the mixing tube from the nozzle head. However, like other direct methods is still an intrusive process that disrupts the production process. An indirect online approach would not disrupt the process.

Indirect methods work by recording specific responses linked to wear of the abrasive waterjet nozzle, for example, noise levels, vibration or change in jet diameter [5]. For waterjet machining, it is possible to split the indirect methods into three groups: monitoring the workpiece's response, focusing on the jet of water, or focusing on the nozzle itself.

Several authors have focused on measuring the response of the workpiece. Kovacevic et al. found a relationship between workpiece normal force measured by a dynamometer and mixing tube wear, with force increasing with wear [5]. Hreha et al. used acoustic emission sensors mounted directly onto a steel workpiece [7]. While the signals captured by monitoring the workpiece material has the potential to detect wear, the process lacks robustness as the responses are workpiece dependent.

Several researchers monitored the jet of water itself. The state of wear of the nozzle and water pressure both influence the jet diameter [8]. Optical vision systems monitoring jet diameter were found to be viable in wear detection [9]. However, as noted by Prijatelj et al., jet spray and abrasive sticking to the lens limit the process [9]. For a harsh environment where the jet of water may not always be visible the method of monitoring the jet directly is impractical. Frequent cleaning of the camera lens may be required leading to process intervention.

Finally, indirect methods can focus on the nozzle itself. Kumar et al. found that accelerometers mounted to the nozzle can detect differences in mixing tube diameter [10]. Kim et al. and Prabu et al. found that the root mean square of the acoustic emission signal can be used for wear detection [11], [12]. Infrared thermography was studied by Kovacevic et al., with progressive mixing tube wear leading to changing nozzle temperatures due to changes in friction between the jet and mixing tube [13]. Louis et al. measured the pressure loss in the abrasive hose and correlated the data with airflow measurements, observing a difference with changing mixing tube exit diameter [14]. Putz et al. found that airflow data can be used for orifice condition monitoring [15]. However, Putz et al. attached the sensor within the abrasive hose without feeding abrasives, an online process monitoring system would require a different setup.

Airflow sensors can also be used for detection of abrasive blockage, tube and orifice misalignment and leakage in the abrasive hose [16]. Airflow sensors are promising for waterjet monitoring application if the setup can be improved as they offer a low-cost solution and have the capacity to detect multiple failures.

This group of research demonstrates that multiple approaches can be used to monitor the waterjet process online in a non-intrusive manner. However, the research has not evaluated the performance of indirect methods in predicting wear, instead concentrating on illustrating their potential in monitoring applications. Although one study by Mohan et al. did explore prediction capability using an indirect approach, its validation was limited [17]. The authors in this paper used the same mixing tubes for training and testing model performance with no clear validation performed on independently sourced data. In addition, performance of predictive models using indirect methods needs to be benchmarked against a more straightforward approach, such as measuring wear time, which would justify using more complicated setups.

2.2. Mixing tube wear

The mixing tube has a long life, capturing the full extent of wear is taxing in terms of time and cost [18]. One potential solution is to accelerate the wear process for data collection. Accelerated wear can be carried out using either a hard abrasive or a soft nozzle material [4]. Although economical, accelerated wear may result in a different wear pattern being observed.

Hashish observed two wear patterns in the mixing tube, as seen in figure 1 [19]. If using a soft mixing tube material such as steel, a divergent wear pattern is observed, with a convergent pattern observed with harder mixing tube materials such as tungsten carbide [19]. The two dominant wear modes are erosion by particle impact at the upstream and abrasion at the downstream sections of the tube [19]. In convergent wear, the wear pattern has wave zones due to jet turbulence inside the mixing tube [3], [11].

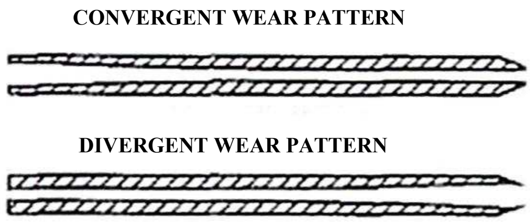

Fig. 1. Possible wear patterns of abrasive waterjet mixing tubes – adapted from [19].

In industry, tungsten carbide mixing tubes, such as the ROCTEC 100, are used as they have a more extended tool life [3], [20]. Nanduri et al. successfully performed accelerated wear tests of tungsten carbide tubes using aluminium oxide [1], [3]. Hashish found that using aluminium oxide leads to greater abrasion but similar erosion inside the tubes compared to industry-standard garnet abrasive because the two materials are similar in density and particle shape, but aluminium oxide is harder [19].

Although the wear profile might show greater abrasion when using aluminium oxide, the wear pattern will remain convergent [19]. Meanwhile, the tool life will be reduced from 100 hours to close to an hour [3]. Accelerated wear trials can be a potential solution for feasibly building a process monitoring system.

To measure the wear of the nozzle, the nozzle weight, inner profile and exit diameter can be measured. Although the exit diameter cannot capture the wear propagating from the top of the tube, it is the simplest and most practical direct method. Exit diameter wear also directly impacts multiple machining characteristics, including critically, the width of the cut [19]. What constitutes a worn tube will vary by application, for example, cutting or precision drilling. It can vary between 10-25% of exit diameter growth [19].

3. Methodology

3.1. Designing a framework for data collection

From the literature review, an indirect approach is selected as an appropriate method for online process monitoring of the waterjet system. Airflow sensors offer great potential and will be investigated in this study as they can detect wear and are affordable. However, previous research found issues with the setup. Instead of adding the sensor to the abrasive supply hose, it can be placed at the air inlet near the abrasive tank, as shown in figure 2. This allows the sensor to work online with abrasive flowing through the system without damaging it. This proposed solution overcomes the initial challenge of designing a non-intrusive and practical monitoring system.

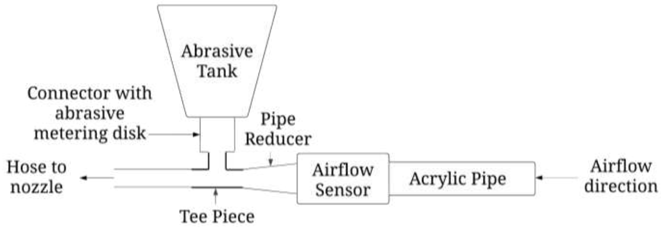

Fig. 2. Drawing of the airflow sensor setup.

In previous research, data was collected with abrasives flowing through the system [5], [7], [10]–[13], [17]. However, data can be collected in a novel manner during the dwell cycle. The dwell cycle is a stage of waterjet machining when the jet is started, but the abrasive supply is not turned on. This stage is performed before waterjet machining operations to generate a vacuum in the nozzle, which will draw abrasives to the nozzle head. This approach allows for a simplified setup without abrasive flowing through during data collection. Recording data during the dwell cycles also allows for tool state prediction before the machining process begins, making the approach highly practical for real-time process monitoring. Additionally, this approach offers potential in building a foundation for tool path compensation in waterjet machining. The tool can be offset for better performance if the exit diameter is predicted before machining.

Finally, accelerated wear was investigated for economic data collection to address the challenge of extended tool life. Aluminium oxide abrasives were used instead of garnet to accelerate the wear process. The mixing tubes used were ROCTEC 100. Using these tungsten carbide tools with harder abrasive was expected to keep the wear pattern consistent with regular wear.

For this trial, two tubes were investigated. Data collected for the first tube would be used to train machine learning models, with the second tube data used to evaluate the models' performance.

To build the dataset for process monitoring, dwell response data was collected from 0 minutes of wear every 10 minutes until the tube was worn for 60 minutes. This time range was selected based on accelerated wear trials completed by Nanduri et al. [3]. By collecting data throughout the tubes' lifecycles, a more extensive dataset could be built up using each tube.

The tubes were worn at 4000 bar pressure with an abrasive supply rate of 7.6 g/s and an abrasive mesh size of 80. During the dwell cycles, data was collected for three repeats using pressures between 3000 – 5000 bar in 500 bar increments. The data under additional pressure was collected to increase the dataset size to help the machine learning models learn patterns within the data. When evaluating model performance, only 4000 bar pressure data was used.

3.2. Experimental setup

The data collection was carried out on an Aquarese 6-axis abrasive waterjet with a Staubli TX200 robotic arm. Professional technicians carried out the data collection under the supervision of the authors.

An airflow sensor was attached to a tee piece connected to the abrasive tank, as shown schematically in figure 2. The sensor used was an SFM3000 by Sensirion. It was connected to the tee piece via a custom 3D-printed pipe reducer. An acrylic pipe of the same internal diameter was attached to the sensor inlet to provide laminar airflow to the sensor. The pipe was 300 mm long, as recommended by the sensor supplier. Data was recorded at a 100 Hz sampling rate for at least 5 seconds during each repeat.

The exit diameter was recorded before each dwell cycle to measure the extent of wear. Steel pin gages were used in increments of 0.01 mm.

The selected tubes were of standard commercially available sizes of 101.6 mm length and 1.0 mm internal diameter.

The ruby orifice used was 0.406 mm in diameter, consistent with the recommended orifice-to-mixing tube ratio found in literature [21], [22].

3.3. Data processing and analysis

To build machine learning models, the raw airflow data was tabulated using time- and frequency-domain features. The raw data for each tabulated row included four-second recordings from jet start. The final training set had 105 rows of data, while the test set had 21 (as it only included 4000 bar pressure data).

The tabulated data was standardized, based on the training dataset by removing the mean and scaling to unit variance. This is a common requirement for multiple algorithms tested.

Machine learning models were built for two tasks: regression and classification. The regression task focused on predicting the exact exit diameter of the mixing tube. The classification task focused on predicting whether the tube was considered worn. 1.1 mm exit diameter was selected as the threshold for wear – a 10% increase from the initial starting diameter of 1.0 mm.

A basic model using wear time, as a sole feature, was built for regression and classification as a baseline for machine learning models, which relied solely on airflow data. The aim was to assess the machine learning models' ability to predict wear when mixing tube usage is not being tracked, as can be found in practice.

For exit diameter prediction and tool state classification the following algorithms were tested: support vector machines (SV) [23], [24], random forests (RF) [24], [25], gradient boosting machines (GB) [24], [26], XGBoost (XGB) [27], LightGBM (LGBM) [28], CatBoost (CB) [29], extremely randomised trees (ET) [24], [30], and k-nearest neighbors (KNN) [24], [31]. For tool state classification, two additional models were used: logistic regression (LR) [24], and TabPFN [32].

For exit diameter prediction, the basic wear time only model (TM) was trained using linear regression. For tool state classification, LR was used instead.

Feature selection was carried out by studying the multicollinearity of features as well as feature importance.

All experiments, including model selection, were conducted using cross-validation solely on the training set. The test set was excluded from these stages to serve as a separate data pool for model performance validation.

4. Results and discussion

4.1. Data collection framework

Figure 3 presents the wear progression of two tungsten carbide mixing tubes. The observed exit diameter wear progression on the tubes suggests the accelerated approach successfully reduced the tool life. The wear pattern was convergent, as shown in figure 4 and exhibited an abrasion wave pattern consistent with literature.

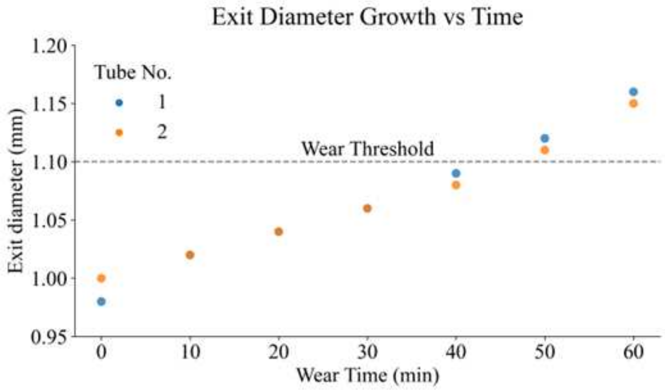

Fig. 3. Comparison of exit diameter growth of ROCTEC 100 mixing tubes during an accelerated wear trial using aluminium oxide abrasive. The wear threshold, beyond which the tool is considered worn, is crossed after approximately 45 minutes of wear.

Fig. 4. Worn mixing tubes 1 (top) and 2 (bottom) after longitudinal sectioning using electrical discharge machining (EDM). The EDM wire was offset to get one perfect half that is displayed above.

However, figure 3 suggests that the exit diameter wear progression is linear, which is inconsistent with a previous study which found a non-linear trend for a convergent wear pattern [1]. This discrepancy may be due to the authors wearing a shorter mixing tube of 50 mm in length. As figure 4 indicates, the wave pattern tends to be more pronounced for shorter tubes, with larger waves appearing around halfway down the tube (at approximately 50 mm mark).

The results align with previous research findings, indicating that using aluminium oxide abrasives yields a similar wear pattern produced when using garnet [19]. Confirming that accelerated trials are a potential solution for the long tool life challenge when developing a mixing tube process monitoring system.

As for the airflow sensor, changes in its signal were observed during the dwell cycles, as seen in figure 5. The signal's magnitude increased with the growing exit diameter, as shown in figure 6. This suggests that increases in exit diameter allow a wider jet of water to leave the mixing tubes, increasing vacuum in the nozzle head and suction in the abrasive hose, pulling more air to the nozzle. Based on these results, the airflow sensor seems suitable for use in an indirect, online waterjet process monitoring system.

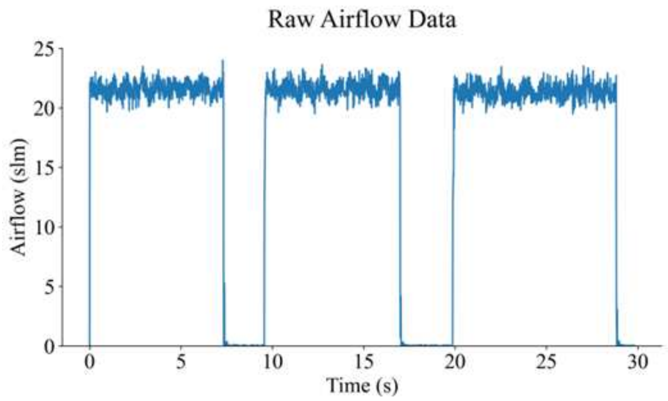

Fig. 5. Raw airflow signal during three dwell cycles of an unwon mixing tube at 4000 bar pressure.

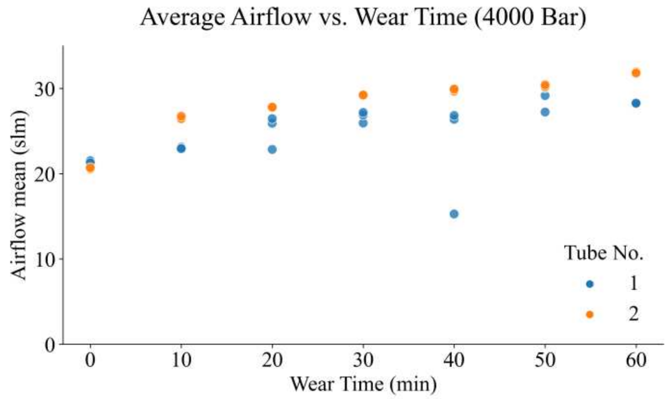

Fig. 6. A comparison of average airflow for each of three repeats during dwell cycle recordings at different wear times at 4000 bar pressure for two worn tubes. An anomaly observed at 40 minutes in tube 1's first repeat wasn't used for model training and was likely caused by abrasive blockage.

The airflow data seen in figure 6 varies more between repeats for tube 1 compared to tube 2. This may be due to data collection imperfections. During data collection, it was observed on the data dashboard that the pressure pump was not always achieving the required pressure before the operator ran the dwell cycle. This could have resulted in lower airflow for the start of the signal.

In addition, for the first repeat, there may have been abrasive still in the hose after the wear cycle. This abrasive blockage may have reduced airflow until it cleared through the system with the generated vacuum.

In future work, the data collection process should allow enough time for the pump to reach the desired pressure value and stabilise before running the jet. In addition, after each wear cycle with abrasives, all abrasives must be allowed to clear through the hose before the water jet is turned off to avoid blockages.

The framework for data collection is promising, but further investigation is required. The dataset so far is limited to only two testing tubes. In addition, this process does not account for mixing chamber or orifice wear. The effect of wear on both parts on the airflow response should be studied.

4.2. Tool condition monitoring

Figure 7 presents the results of different regression models. The linear time-based model outperformed sensor-based machine learning models. The time model had a MAE of 0.01. The metric suggests on average, errors are 0.01 mm. The best performing machine learning model had a MAE of 0.02. 0.02 mm wear would equate to approximately 6 hours of machining time during regular wear at 3000 bar pressure and an abrashive feed rate of 6g/s [33]. The input parameters are not an exact comparison, but this figure indicates the rough tool life error from this prediction – if using the exit diameter as a threshold for deciding the condition of the tool.

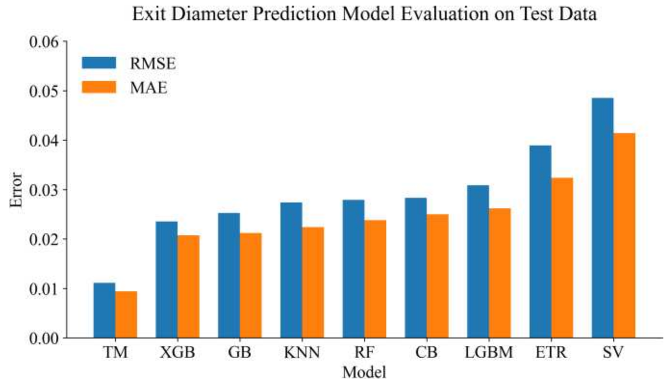

Fig. 7. Comparison of model performance when predicting exit diameter wear of unseen data in the test set. The models were evaluated using RMSE and MAE metrics, with lower scores indicating better performance. Both metrics use the same scale as the data being measured. Machine learning models using airflow data were outperformed on this dataset by a linear regression model (TM above) based on wear time. XGBoost was the best performing machine learning model with an RMSE of 0.024 and MAE of 0.021.

For tool state classification, a wear time-based model performed better than models trained on airflow data, as seen in figure 8. TabPFN and LR models proved to be the best on this dataset with an accuracy score of 90%. TabPFN, a pre-trained transformer model had the highest overall performance, suggesting pre-trained deep learning networks can be leveraged for small tabular datasets.

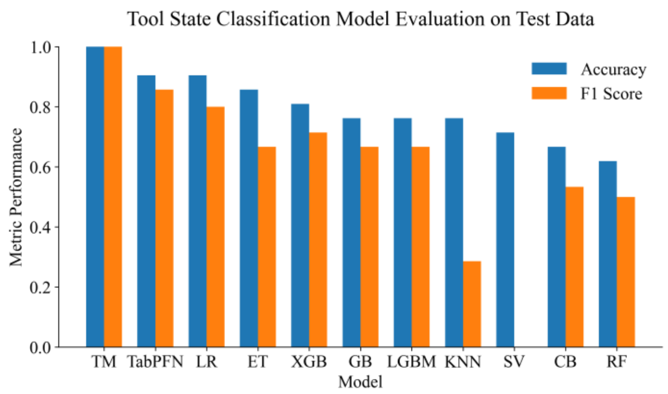

Fig. 8. Comparison of model performance when classifying whether the tool has worn past the predefined threshold of 1.1 mm exit diameter. The models were evaluated using accuracy and F1 score, with a higher score indicating better performance. The model using time as a sole parameter outperformed machine learning models using airflow data to classify the state of the tool. TabPFN, a pre-trained deep-learning model was the best performing machine learning approach with an accuracy of 0.9 and an F1 score of 0.86.

The findings indicate that a simple approach of tracking the mixing tubes' operational duration may prove sufficient and potentially more effective for wear detection than more complex methodologies. However, it's crucial to acknowledge the limitations imposed by the small dataset, which included two worn tubes. A larger dataset may reveal greater variation in the exit diameter over time than observed in this study, potentially reducing the performance of the wear time models.

In addition, it was noted that the airflow data for the training set mixing tube was unstable. As the data collection process is refined, the data quality will likely improve, reducing noise and allowing the machine learning models to learn the patterns within the data better.

Furthermore, models solely based on wear time may not adequately adapt to changes in the process. For instance, issues such as blockages, poor abrasive flow or process parameter adaptations could worsen the time-based models' performance.

5. Conclusions

The study presented a novel approach for building a waterjet process monitoring system. Using aluminium oxide abrasives enabled accelerated wear and fast data collection while keeping the mixing tube wear pattern consistent with regular wear. A unique method for data recording during the dwell stage of waterjet machining was introduced. This simplified the process, eliminated flowing abrasives, and allowed for predictions to be made prior to machining, which could serve as a foundation for tool path compensation. Finally, the data collection process revealed that airflow sensors can detect changes in exit diameter.

Furthermore, the performance of machine learning models using airflow data was compared to simpler wear time-based models for exit diameter prediction and mixing tube state classification. While simpler models performed better in this study, their adaptability to process changes, like poor abrasive flow, may be limited. More complex methodologies using sensor data and machine learning may be necessary to improve wear detection in the future.

This paper presents a promising framework for developing a mixing tube process monitoring system. However, further research is required to understand the impacts of various factors, such as orifice and mixing chamber wear, on prediction capabilities. The limitations of a small dataset also need consideration. Broader testing with more tubes is recommended. Finally, future work should assess how models trained on accelerated wear data perform with regular wear trial data.

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